Corporate Credit Rating Prediction Using Deep Learning

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จุฬาลงกรณ์มหาวิทยาลัย
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วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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การจัดอันดับเครดิตองค์กรมีบทบาทสำคัญในการลดข้อมูลที่ไม่สมมาตรระหว่างนักลงทุนและผู้กู้ และช่วยเหลือนักลงทุนโดยแสดงถึงของประสิทธิภาพในการดำเนินธุรกิจและความน่าเชื่อถือขององค์กร เพื่อให้นักลงทุนสามารถตัดสินใจลงทุนในสินทรัพย์ของบริษัทได้อย่างเหมาะสม สถานการณ์ทางเศรษฐกิจได้ส่งผลลบต่อภาคธุรกิจต่างๆ และยังส่งผลให้อันดับเครดิตของบริษัทเกิดการเปลี่ยนแปลง ทำให้เกิดปัญหาในการปรับกลยุทธ์การลงทุนและนำไปสู่การขาดทุน เนื่องจากมีช่องว่างระหว่างระยะเวลาในการประกาศการเปลี่ยนแปลงอันดับเครดิตอย่างเป็นทางการและการเปลี่ยนแปลงอันดับเครดิตจริง งานวิจัยนี้นำเสนอทางเลือกในการทำนายอันดับเครดิตโดยใช้โมเดลการเรียนรู้ด้วยเครื่อง เช่น Support Vector Machine (SVM), Linear Regression และ Deep Neural Network (DNN) ผลลัพธ์ที่ได้แสดงให้เห็นว่าโมเดล Deep Neural Network นำเสนอประสิทธิภาพได้ดีเทียบเท่ากับโมเดลการเรียนรู้อื่น

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Corporate credit rating has an important role in reducing asymmetric information between investors and borrowers and assisting investors as a signal of the entities' performance and creditworthiness for making appropriate investment decisions in a company's assets. The economic distress has negatively affected various businesses and resulted in company rating transitions. This led to a problem in adjusting investment strategy and a serious loss as there is a lack of time between officially announced credit rating transitions and real transition. This study provides alternative methods for credit rating prediction by applying machine learning models; Support Vector Machine (SVM), Linear Regression, and Deep Neural Network (DNN). The result has shown that the Deep Neural Network model presents the comparable performance to other models.

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ขอขอบคุณ SETSMART และ TRIS Rating ในการให้ข้อมูลที่นำมาใช้ในการวิจัยครั้งนี้

สุดท้ายนี้ขอขอบคุณครอบครัวและกัลยณมิตร ที่สนับสนุนและให้กำลังใจในการเรียนระดับปริญญาโท และในการทำวิทยานิพนธ์เสมอมา

Napasorn Thavichaigarn

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Chapter 1 Introduction

1.1 Introduction

A company's credit rating is essential in reducing asymmetric information between investors and borrowers. Investors can perceive credit ratings as a signal of the entities' performance and creditworthiness. Credit rating creates confidence for investors and allows them to make suitable investment decisions in the company's assets, especially for those who invest in fixed assets.

In Thailand, the credit rating of companies is mostly assessed by two credit rating agencies: TRIS Rating Company Limited and Fitch Ratings (Thailand) Company Limited. By measuring the ability to pay debts in both interest payment and principal repayment, the rating is ranked from Investment Grade (AAA to BBB-) to Non-Investment Grade (BB+- to D) compared to the Thai government bonds benchmark. To determine corporate credit rating attributes generally used consist of

1. operating risk, including business trends, company's policy, peers' comparison
2. financial risk from financial statements relies on the quality of financial information and research on historical data to create a financial projection
3. financial ratio analysis including profitability ratio, economic structure and source of fund, liquidity ratio, and operating ratio focusing on each business sector and verified by committee.

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The credit rating is assigned via committee voting and agreement and normally be applicable over 3-5 years. Furthermore, bond credit rating is considered from corporate credit rating and will mostly be one notch lower than the corporate credit rating assigned. Although the traditional method of credit rating considerations includes many numerical calculations and analyses, there are limitations as the approach relies on committee considerations for every ending process, economic pattern, and business trend no longer behave as usual and requires instantaneous adjustment of credit rating, which human judgment struggles to provide the same accuracy as in average and may need tools to help following instantaneous adjustments during the economic crisis.

Artificial intelligence, such as machine learning, is another option to track a company's performance and predict the real-time credit rating transition. The economic distress has caused problems in business operations and led to the inability to pay old debts due to the underperformance of business and revenue generated. The company, therefore, requested to extend the repayment term for both principal and interest by offering additional benefits for bondholders, such as increasing interest rates or issuing new bonds to pay off outstanding debts. With the size of the current bond market and the increased value of definitive bonds, the process of debt repayment monitoring has become more complicated. Therefore, machine learning becomes a company's performance monitoring solution.

There are numerous pioneering experiments in applying machine learning models to explore and achieve the best solution for the credit rating approach. For example, Cao and his team [17] used a support vector machine for the bond credit rating problem. This later influenced the work of Golbayani and his colleagues [10], which applied decision trees and support vector machines for credit rating issues. Moody and his research group [1] finally proposed a strategy to select the most appropriate architecture for corporate bond prediction. This heuristic prediction strategy combines the number of hidden units' selection and weight elimination for neural network construction and pruning. The adoption of neural networks was then utilized for credit evaluation by Angelini and his research team [7].

This research has proposed to apply three machine learning models: support vector machine (SVM), linear regression, and deep neural network (DNN) to predict corporate credit rating to improve and raise the accuracy of corporate credit rating prediction, assisting regulate of the capital market, and monitoring debt payment capability in aspect to benefit investors, financial institutions, credit rating agencies, regulators, and others. We obtain data from TRIS rating agency as the agency provides most complete credit rating data for the corporates in Stock Exchange of Thailand. We also observe the best normalization technique to increase the performance of all models. The remainder of this thesis is organized as follows.

Chapter 2 provides a review of related techniques for corporate crediting rating predictions. The prior works of applying the machine learning model to the financial problem are explained in Chapter 3. Chapter 4 presents the proposed three machine learning models for predicting credit rating and describes the experimental data set, the feature selection, and the preprocessing method. The practical result and performance evaluation of the proposed approaches is provided in Chapter 5. The discussion of experimental result is provided in Chapter 6. Finally, the conclusion is presented in Chapter 7.

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Chapter 2 Related Theory

2.1 Machine Learning Model

2.1.1 Support Vector Machine

Support Vector Machines have been used in several applications, e.g., pattern recognition for handwritten detection, face detection, and text categorization. The supervised learning algorithm based on statistical learning frameworks (VC theory) aims to find an optimal hyperplane in N-dimensional spaces in which N refers to the number of features. Given an example of two input features, the hyperplane acts as a classifier providing maximum distances between support vectors to be classified accurately.

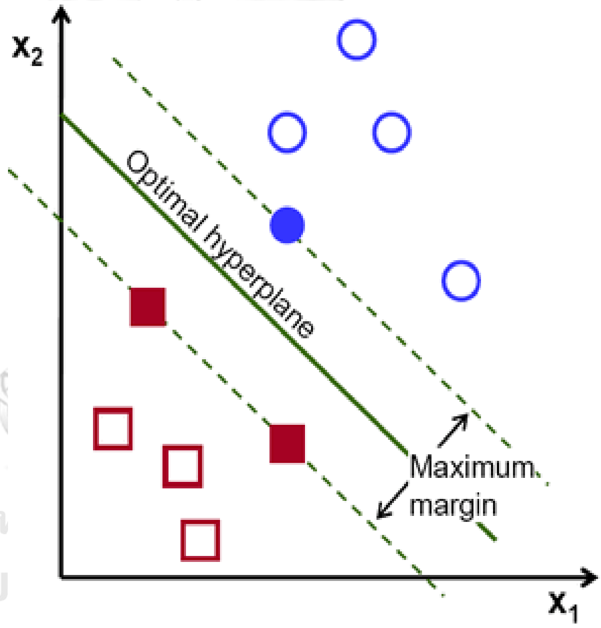

Figure 1: A possible hyperplane that presents the maximum margin for two input variables

Source: towardsdatascience website

The algorithm can be incorporated as a versatile solution for various problems. The model still has limitations in the kernel's choice [3]. To successfully use linear classifiers in solving nonlinear problems, selecting the appropriate kernel offer a way to avoid complex calculations and assist in determining hyperplane shape and decision boundary. The standard type of kernel used can go from linear to polynomial. The universal function of the Gaussian radial basis function performs well with a smaller data set and assists in avoiding overfitting. This kernel also requires no prior knowledge of the data set. The equation of kernel is show in (1).

$$K\left(x_i, x_j\right) = exp\left(-\gamma \parallel x_i - x_j \parallel\right)^2 \quad (1)$$

2.1.2 Linear Regression

The linear regression model consists of the assumption that input features and output features can be explained using a linear relationship as the unknown parameter of the coefficient, as the intercept, and as the random error component. The formula can be arranged into vectors (2) and (3) with and employing the method of least squares to estimate the coefficient parameter by minimizing the residual sum of squares.

$$Y = \beta_0 + \sum_{j=1}^{p} X_j\beta_j + \mathcal{E} \quad (2)$$

$$RSS(\beta) = \sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} X_j\beta_j)^2 \quad (3)$$

2.1.3 Deep Neural Network

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Deep learning (DNN) is a subset of machine learning which mimics the working process of neural networks by creating multilayer networks for complex data analysis and increasing prediction efficiency. DNN is defined as a computational model influenced by the learning mechanism in a human nervous system consisting of connected processors called neurons, which creates a sequence of actual activation. Activation starts when the input neuron is activated from the outer environment. The other neurons become activated through weight connections from the former active neurons.

The activation function formula is presented (4). The activation function (ϕ) is provided in several forms which allow estimates of both linear and non-linear functions. The output is known as the post-activation value.

$$\hat{y} = \phi(X \cdot W) = \phi(\sum_{j=1}^{d} w_j x_j) \tag{4}$$

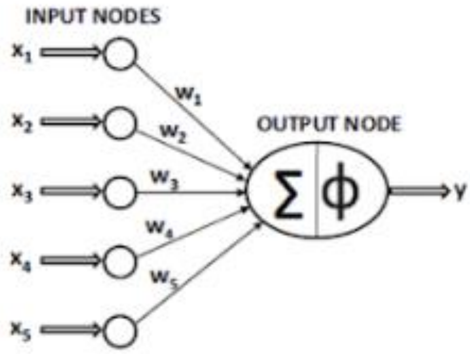

Figure 2: The basic architecture of the perceptron

Source: Neural Networks and Deep Learning, Charu C. Aggarwal

Architectures of most deep learning strategies lie in the following techniques: (i) convolutional neural networks (ii) recurrent neural networks (iii) recursive neural networks and (iv) standard deep neural networks which are applied in this paper. The DNN model consists of three layers as present in figure 1. The tree layers are the input layer, one or more hidden layers, and the output layer. The input layer has nodes that store processed information on features to which the number of nodes refers to important information required. The hidden layers between the input and the output capture and transform the input data from one node to another in the next layer to produce an output. This hidden layer is also described as a black box, as the operation between layers is invisible.

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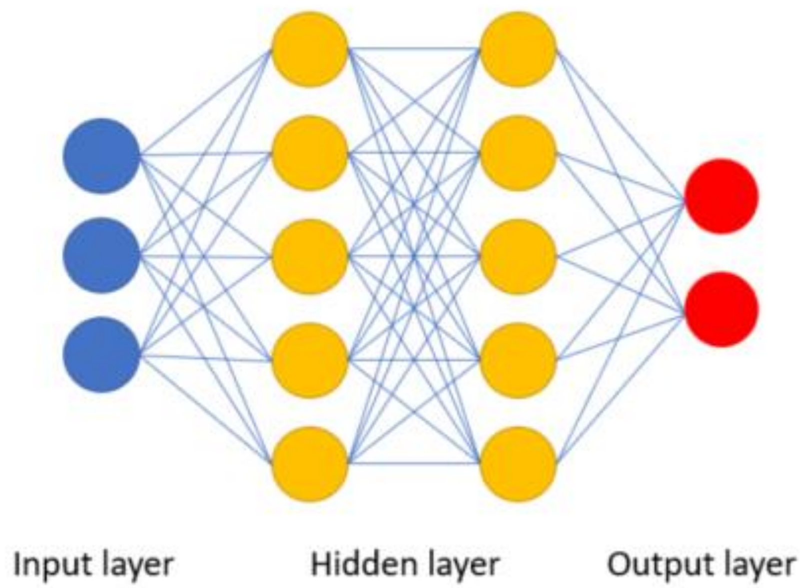

Figure 3: DNN contains three layers: input, hidden, and output.

2.1.4 Cost Function

The cost function estimates a measure of the accuracy of a machine learning model and is used to evaluate the performance of the models. The cost function is calculated by measuring the difference between the prediction value and the actual value received using promising indicators of mean absolute error (MAE) and mean squared error (MSE). The MAE measures the absolute difference between predicted and actual values, whereas the MSE measures the average of the squares of the errors. The formula is given as (5) and (6).

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \tag{5}$$

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n} \tag{6}$$

Chapter 3 Literature Review

In this research, we conducted a study for prior experiments to gather insight into similar techniques used. We classified former research into two categories: those proposed methods for feature selection and data preprocessing and those for utilizing similar SVM, linear regression, and DNN techniques.

The study of Moody and Utans [1] provides the scaling method by assigning a numerical scale for bonds with a rating 'B-' up to 'AAA' before applying it to the model. It has eliminated the 'non-standard' rating for better model performance. They also suggest using few categories as the model may not able to distinguish all 16 rating categories by dropping sub categories of + and – and combine 'AAA' with 'AA'. The result suggested that using ten average financial ratios as input variables cannot represent the firm's performance and recommended more data availability can raise the model's performance. Chaveesuk, R. [6] has extended this concept further by including more specific features of six to ten financial ratios classified into debt ratio, liquidity ratio, total assets, financial strength, and profitability ratio to the mode which perform as essential knowledge for further decisions on financial ratio usage. These suggested including similar types of financial ratios as our feature selection. This research only selects top six rating of bonds which are B to AAA as the lower rating bond are not attractive to investors. The training data set of 60 bond issue companies is randomly select from bond issues of 1996 and contain data of 10 of each rating class. This experiment also randomly selects 30 bond issues in 1997 with data of 5 for each rating as the test set number one and includes 30 bond issues randomly select from training set to the test set number one in order to create test set number two for comparison. Angelini [7] has perform credit assessments on 76 small businesses in Italy across 2001 to 2003 in order to create tools for assisting credit risk internal assessment for the Basel Committee. They introduced essential financial input variables, including circulating capital and stock values which create an advantage to the model The data is classified into two categories of good and default borrowers with criteria of firms following loan obligation at the end of the study period. They also employed logarithmic formula for features normalization as the data set consists of many outliers and this technique can help in avoid losing essential information. This highlight that the suitable normalization technique is recommended for credit rating assessment study. The research split data set into 70% of data as a training set and 30% of data as a test set, balancing data of good and bad borrower for both set. Hajek [9] has proposed a study of corporate credit rating and obtained data sets from emerging markets and comparing with data from other three regions of the EU, The United States, and the other developed countries which is different from other studies where the study is focus on developed markets only. He has used the interval value fuzzy rule-based system with tuning and rule selection (IVFRBs) to predict both investment and non-investment grade and obtain financial data from Reuters Global Market over 2008 to 2010. The input selection is based on valuation ratios, dividend, financial strength, and profitability ratios. He also introduced the idea of separating investment grade and non-investment grade for better performance by using return yield for investors. The result suggests on adding industry specific growth trends and market structure. Also, the models are more preferable to data from the developed countries over the emerging countries due to the misbalancing of data.

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In addition, Moody and Utans [1] proposed a heuristic strategy to find the best method for selecting a neural network model for the corporate bond rating problem including adopt the method of nodes selection via sequential network construction, sensitivity base pruning of inputs, and optimal brain damage (OBD) pruning for weight. They observed the prediction risk to determine the final network and adopted both predictions squared error (PSE) and nonlinear cross validation (NCV) to estimate prediction risk. The result suggest that non-linear network has outperformed the linear regression. Chaveesuk R's research [6] supports using the neural network to solve problems containing complex and imperfect data relationships as the model does not require prior function form and mostly learns from input-output examples training. This research explored the most well-known supervised neural network of backpropagation, radial basis function, and learning vector quantization for U.S. corporate bonds. The result shows that neither model present well accuracy. However, the performance of neural network is comparable with the logistic regression model and suggest the use of mathematical approach in combine with neural network model. Angelini [7] explored a feedforward neural network and a special purpose neural network to perform credit assessments on 76 small businesses. The result suggests that both models provide accuracy for credit prediction with a low error. The findings of Bahrammirzaee [8] of observing three artificial intelligent technique; ANN, ES, and hybrid intelligent system for three domain of financial markets including credit evaluation, portfolio management, and financial planning suggest that artificial neural networks are robust solutions for many finance applications. It has outperformed or is comparable to the conventional method, such as a decision tree or logistic regression for credit rating evaluation. However, there are some limitations for neural network model such as taking too much time to converge. The research suggests using conventional method with neural network to create hybrid method give the best result for prediction. To estimate the accuracy of prediction, a notch distance method which measures the difference between credit rating prediction and initial credit rating, is proposed by Golbayani [10]. This experiment applies the fundamental model, such as a decision tree and support vector machine. Traditional models' results are compared with a more advanced approach, such as an artificial neural network. The random forest has outperformed the advanced model using notch distance methodology to assess. Later, Golbayani [21] also adopted an artificial neural network model in the experiment of corporate credit rating data treated separately into three sectors: energy, healthcare, and finance. They employed multilayer perceptron (MLP), convolutional neural network (CNN), and long short-term memory (LSTM) to predict

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corporate credit rating data. The results show that LSTM has outperformed other models by using all the financial variables and allowing the neural network models to select, giving the model the best performance. Stephe, F. [11] has attempted to study the relationship between credit rating transition and default events. The Cox hazard regression model is employed to observe credit default events by obtaining credit data during 1970-2002 from Moody's Default Research Database. The credit rating drift of firms has reflected the default's intensity, and there is an aging effect for which firms that have been rated for an extended period have more tendency to default than recently rated firms.

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Chapter 4 Methodology and Dataset

4.1 Proposed Method

The proposed methodology of this research entails evaluating and comparing the predictive performance of three models: Support Vector Machines (SVM), linear regression, and Deep Neural Networks (DNN) to analyze financial statements data of corporates yearly and predict the credit rating. The models' accuracy is evaluated using MAE and MSE cost functions, which calculate the error between prediction and actual values.

We applied the financial statement data as the input features of the three models to predict the corporate's credit rating. The 17 financial data related to profitability ratios, cash flow, and debt ratios are applied to the models as input features as they are considered to present corporates' performance and their ability to repay debt. The model output is the credit rating of the companies, which we have transformed into numerical code before applied into the models.

4.2 Experimental Dataset

For this research, we collected historical financial data from SETSMART. The study period is from 2016 to 2021, following the 3-5 years of recorded data consideration as fundamental approaches. Credit rating agencies primarily consider the entities' past performance based on financial statements, missed debt repayment, the potential for bankruptcy, cash flow, income, profitability, and current debt levels of the company. All of these factors are recognized to have an impact on credit ratings. The financial ratios, derived from the financial statements, are examined annually since corporate credit ratings are assessed yearly without accounting for immediate business issues. The corporate credit rating data, including investment grade and non-investment grade ratings, was obtained from TRIS credit rating agency's website, a public source.

Selecting 17 financial ratios is based on the previous work [6] [12] and availability on SETSMART in which this research has focused on adopting ratios that present the ability of firms in repaying debt e.g., profitability and liquidity ratio The description of financial data is listed in the table below.

Factor	Description
F1	Change of equity price per year
F2	Return on equity
F3	Total asset
F4	Enterprise value
F5	Operating cash flow
F6	Investing cash flow
F7	Financing cash flow
F8	Net cash flow
F9	Earnings per share
F10	Net profit
F11	Fixed asset turnover
F12	Total asset turnover
F13	Net profit margin
F14	Current ratio
F15	Quick ratio
F16	Cash cycle
F17	Debt service coverage ratio

Table 1: Description of Financial Data as Features

Following the assessing method of credit rating agencies of comparing the performance of the companies to their historical interpretations, the input features are adjusted into percentages using (7).

$$\%\ Change = \frac{x_t - x_{t-1}}{x_{t-1}} * 100 \tag{7}$$

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Where x_t is the financial data of period interest, and x_{t-1} is the financial data of a year before period interest.

4.2.1 Explanation of Credit Rating

The credit ratings assigned by TRIS range from investment grade (BBB- to AAA) to non-investment grade (B- to BBB), as depicted in the following table. For this research, the credit ratings from TRIS were selected as the data source due to the company's association with the Stock Exchange market of Thailand and the preference for using a local rating agency. It is worth noting that TRIS provides the most comprehensive information available in this context. The explanation on TRIS rating assigned is shown in table 2 below.

Investment Grade	AAA AA+ AA AA- A+ A BBB+ BBB BBB-
Non-Investment Grade	BB+ BB BB- B+ B B-

Table 2: TRIS credit rating assigned

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SETSMART are identified for the corresponding rating data source from TRIS. The firms that lack credit rating data are eliminated from the analysis and remain with only available credit rating information. Companies with ‘no rating’ are also eliminated from the data set, as the previous studies have indicated that the inclusion of companies with no rating lead to noise and negatively impacts the accuracy of model performance.

The experimental set includes 300 data (80 companies) which can be classified for each credit rating class as table 3 below.

Credit Rating	Amount of Data from Annual Financial Statement
AAA	11
AA+	6
AA	12
AA-	14
A+	34
A	43
A-	43
BBB+	46
BBB	36
BBB-	33
BB+	20
BB	2

Table 3: Data Set of Each Credit Rating Class

4.2.2 Data labeling

The letter credit ratings are transformed into numerical codes before applying to the models. This transformation enables the incorporation of credit ratings as quantitative variables in the models. The different methods of assigning numerical

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codes to letter credit ratings are conducted to determine which experimental designs yield a better result. We found that setting all non-investment grade ratings as a consistent numerical value of 11 allows for a more straightforward classification and gives better results than leaving all non-investment grades as separate categories. We also omit the 'no rating' data as it was found to be noise and reduced models' accuracy from the prior experiment. Therefore, the letter credit rating is labeled as table 4 before applying it to all three models.

Credit Rating	Transform Code
AAA	1
AA+	2
AA	3
AA-	4
A+	5
A	6
A-	7
BBB+	8
BBB	9
BBB-	10
Non-investment grade (BB and BB+)	11

Table 4: Transform Code Assigned Non-Investment Grade as a Consistent Number

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4.2.3 Experimental Sets and Data Splitting

Before input data is fed into the models, the data is structured into the training, validation, and test sets. The splitting methodology employed the use of TRIS's method for assessing corporate credit rating, which considers information at the current (T) and compares it to the rating information from the previous year (T-1). For example, a company's credit rating for 2020 is determined based on the credit rating given for the year 2019 and the financial performance of a similar year. Therefore, the credit rating assigned for the year 2020 considers the available rating data from the previous years and the financial performance of the same year (2020). This approach allows the rating agencies to consider the company's historical performance and financial health as crucial indicators while determining its credit rating for the subsequent year.

For the new credit rating assigned, TRIS has used the 56-1 form of the Securities and Exchange Commission of Thailand (SEC), which provides all the financial ratios and financial statements required for credit rating consideration.

4.2.4 Experiment Set 1

For this research, we create two experiments for data splitting. The experiment set 1 is done with purpose to use all the existed rating information of the companies to train models for prediction rating of the same group of companies in the next year (T+1). We separated all data from 2021 as the test set and assigning data from 2016 to 2020 for the training set and validating set. The validating group was created by allocating 20% of the data from 2016 to 2020. The method of splitting data is shown in table 5 as below.

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Year	Training Data	Validating Data	Testing Data
2016 to 2020	76 companies with data available from 2016 to 2020 (See the complete companies list in Table 6)	20% of training data	-
2021	-	-	51 companies with data available in 2021 (See the complete companies list in Table 7)

Table 5: Data of Experiment Set 1

Training Data (Year 2016 to 2020)	A, AH, AMATA, ANAN, AOT, AP, AQUA, ASIAN, BCH, BCP, BDMS, BH, BJC, BRR, CCP, CFRESH, CI, CK, CKP, CPF, CPN, CWT, EA, EP, EPG, ESSO, FPT, GLAND, GLOBAL, GPSC, ICC, INTUCH, IRPC, IVL, JMART, KSL, LALIN, LH, LOXLEY, LPN, MBK, MIDA, MINT, MJD, MK, PF, PREB, PRIN, PTT, PTTGC, QH, RATCH, RML, ROJNA, SAMTEL, SC, SCC, SCCC, SEAFCO, SENA, SGP, SINGER, SIRI, SPALI, SPCG, SYNTEC, THCOM, TMT, TOP, TTCL, TU, UAC, UNIQ, UV, VNG, WHA

Table 6: List of companies for training data in experiment set 1

Testing Data (Year 2021)	AGE, AH, AMATA, AP, AQUA, ASIAN, BCH, BDMS, BH, BJC, BRR, CBG, CCP, CK, CKP, CPF, CPN, CWT, EA, EGCO, EPG, FPT, GLAND, GLOBAL, GPSC, INTUCH, IVL, JMART, LALIN, LANNA, LH, LOXLEY, LPN, PREB, PRIN, PTT, PTTGC, QH, RATCH, ROJNA, SC, SCC, SCCC, SENA, SGP, SINGER, SIRI, SPALI, SPCG, SYNTEC, THCOM

Table 7: List of companies for testing data in experiment set 1

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4.2.5 Experiment Set 2

For the experiment set 2, we designed the experiment using existed rating information of the companies to predict the rating of companies that are not in training set, but in the same period. We have readjusted the test set by excluding eight companies, representing 10% of the entire dataset of 80 companies. The criteria for selecting the test set are based on companies with limited availability of rating historical data. These companies only have credit rating data available for 2020 and 2021, representing the latest years. By selecting companies with little historical patterns, we can evaluate the model's ability to accurately predict credit ratings based on a more restricted dataset that the model has never experienced before. This adjustment leaves us with a training set and validating set comprising 72 companies with data available from 2016 to 2021. The validating set was created as the previous experiment by allocating 20% of data of 72 companies. The method of splitting data is shown in table 8 as below.

Year	Training Data	Validating Data	Testing Data
2016 to 2021	72 companies with data available from 2016 to 2021 (See the complete companies list in Table 9)	20% of training data	AGE CBG CPN EGCO EPG GLAND LANNA SYNTEC (Companies with data available in 2020 and 2021)

Table 8: Data of Experiment Set 2

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Training Data	A, AH, AMATA, ANAN, AOT, AP, AQUA, ASIAN, BCH, BCP, BDMS, BH, BJC, BRR, CCP, CFRESH, CI, CK, CKP, CPF, CWT, EA, EP, ESSO, FPT, GLOBAL, GPSC, ICC, INTUCH, IRPC, IVL, JMART, KSL, LALIN, LH, LOXLEY, LPN, MBK, MIDA, MINT, MJD, MK, PF, PREB, PRIN, PTT, PTTGC, QH, RATCH, RML, ROJNA, SAMTEL, SC, SCC, SCCC, SEAFCO, SENA,, SGP, SINGER, SIRI, SPALI, SPCG, THCOM, TMT, TOP, TTCL, TU, UAC, UNIQ, UV, VNG, WHA

Table 9: List of companies for training data in experiment set 2

4.3 Data Preprocessing

We normalize the data using Min-Max normalization (8) for both input features and output to create the same scaling for model comparison purpose for support vector machine and linear regression model. We have used batch normalization (9) in deep learning models to improve the training process and enhance the model's performance. This normalization is applied during the training phase, specifically within each mini batch of data. The primary objective of batch normalization is to normalize the input values within a mini batch, making the data distribution more stable and reducing the covariate shift. This helps the model converge faster and allows for better generalization [13]. Furthermore, the batch normalization also reduces need of irrelevant data dropout.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (8)$$

The process of batch normalization (9) includes two steps. First, the mean and standard deviation of the input data are calculated. The input data is normalized using these statistics by scaling and shifting them to obtain zero mean and unit variance. This is to ensure that the model become less sensitive to variations in input data distributions. The learnable parameters of gamma and beta (10) (11) also include in the batch normalization and allow model to adapt and scale the normalized value to achieve optimal result.

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$$\hat{x}^{(k)} = \frac{x^{(k)} - E[x^{(k)}]}{\sqrt{Var[x^{(k)}]}} \tag{9}$$

$$\mu_B \leftarrow \frac{1}{m}\sum_{i=0}^{m} x_i \tag{10}$$

$$\sigma_B{}^2 \leftarrow \frac{1}{m}\sum_{i=0}^{m}(x_i - \mu_B)^2 \tag{11}$$

We have attempted to use the method of z-score normalization to compare with min-max normalization. However, we observed that the z-score normalization presents a high MAE score for all three models using data splitting method of both experiment 1 and experiment 2. This MAE result shows that the z-score normalization does not perform well in increasing model accuracy and should not be chosen as the normalization technique for this experiment. From this result, we have decided that min-max normalization and batch normalization are the most appropriate normalization technique for this experiment.

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Chapter 5 Experimental Result

5.1 Features Correlation

To study relationship between features and for input data and output data, the statistical correlation method is performed. The correlation of features close 1 present the high correlation between features. Figure 4 below shows the correlation between the input and output features for this experiment. The features with the highest positive correlation to the output are investing cash flow, financing cash flow, and precent change of quick ratio. The features that present a strong negative relation with the output are net profit, operating cashflow, EPS, and percentage change of ROE.

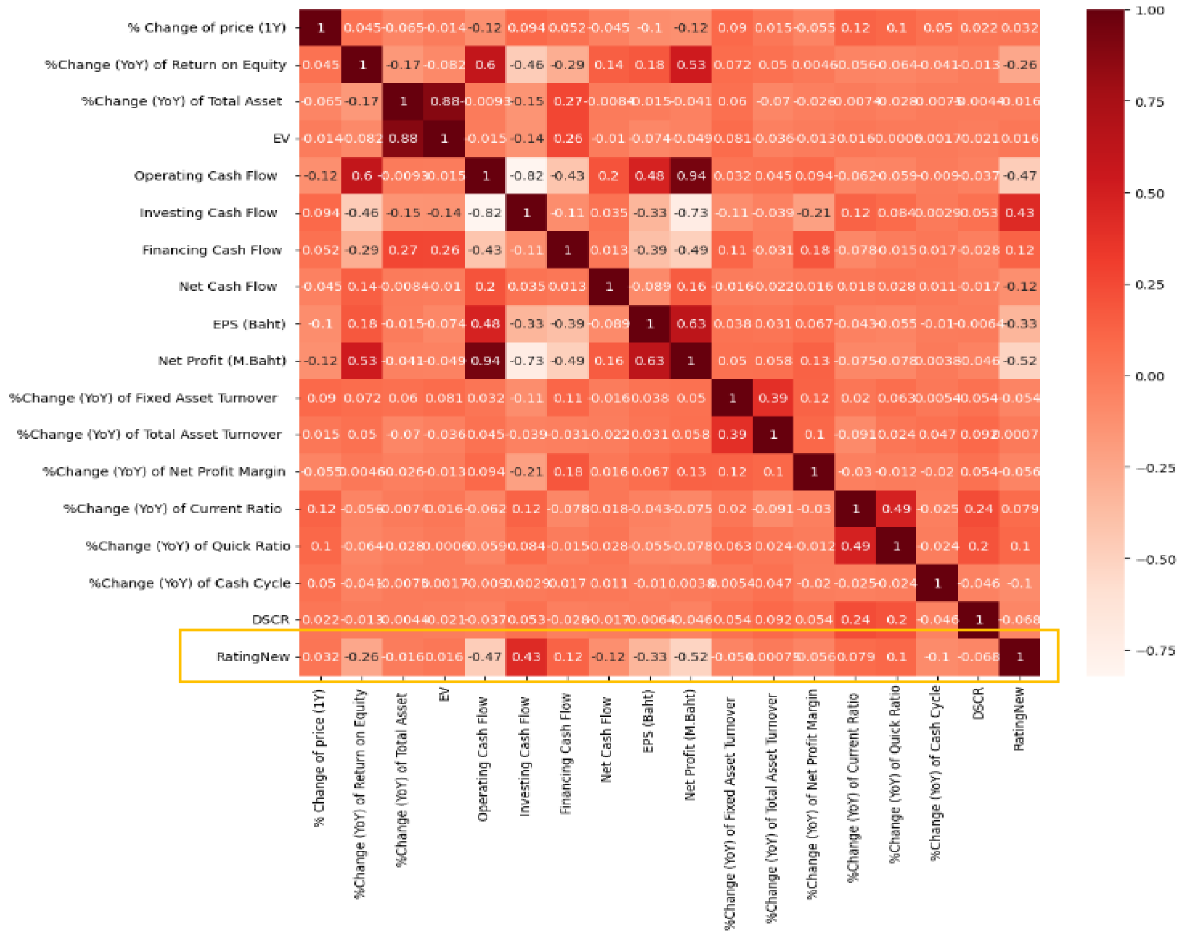

Figure 4: Correlation between the input variable and the output variable

5.2 Prediction Performance Between Models

We conducted the experiment using three machine learning models: SVM, linear regression, and DNN for two experiments which assigned different test set and training set. The result of the two experiments is evaluated using two methods of MAE and MSE. The table 10 and table 11 below show configuration of linear regression and DNN model. We employed the use of Adam optimizer and stopping algorithm. The linear regression is set at 200 epochs which means that the maximum train is 200 and the training process may stop before 200 epochs if a convergence criterion is met. The DNN is set at 200 epochs also and the training process may also stop before 200 epochs if a convergence criterion is met.

Parameters	Configurations
Optimizer	Adam
Activation	ReLu
Learning rate	0.001
Stopping algorithm	200 epochs (or less if converge before)

Table 10: Configurations of Linear Regression

Parameters	Configurations
Optimizer	Adam
Activation	ReLu, Sigmoid
Learning rate	0.001
Stopping algorithm	200 epochs (or less if converge before)

Table 11: Configurations of DNN

The output layer receives all information for linear regression and indicates the output. The architecture of linear regression and DNN model are presented as below. Figure 5 presents the architecture of linear regression model consists of two dense layers. The first layer has 64 units and uses the ReLU activation function, while the second dense layer has 1 unit. The normalization layer does not appear here as the data has been normalized with min-max normalization prior to training.

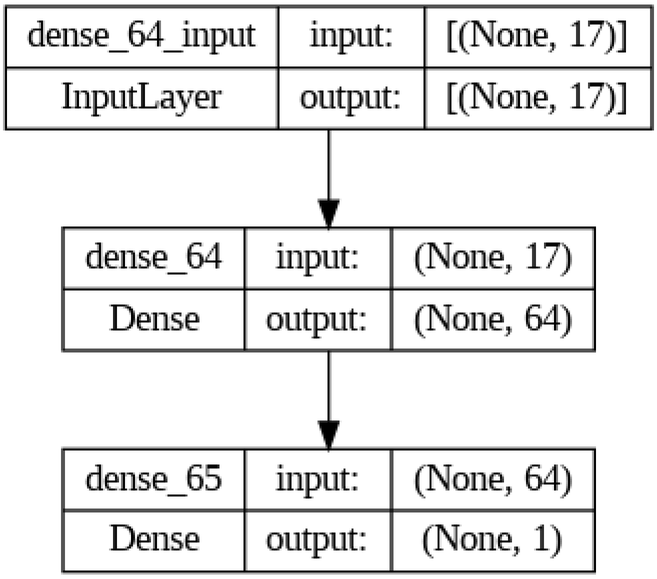

Figure 5: Architecture of linear regression

Figure 6 below shows the architecture of DNN model with 4 layers. The first layer and the second layer have dense layer of 64 units and use the ReLu activation function. The third and fourth layer have dense layer of 128 units and use the ReLu activation. Between each layer, the batch normalization technique is applied to normalize the activation of the previous layer and make the training process more stable. This assists in standardize the input and improve overall performance of the model. We also include the dropout technique to mitigate overfitting by setting dropout rate at 0.2 which means that 20% of the input units will be randomly set to 0 at each update. This prevents the model from relying on the particular set of neurons.

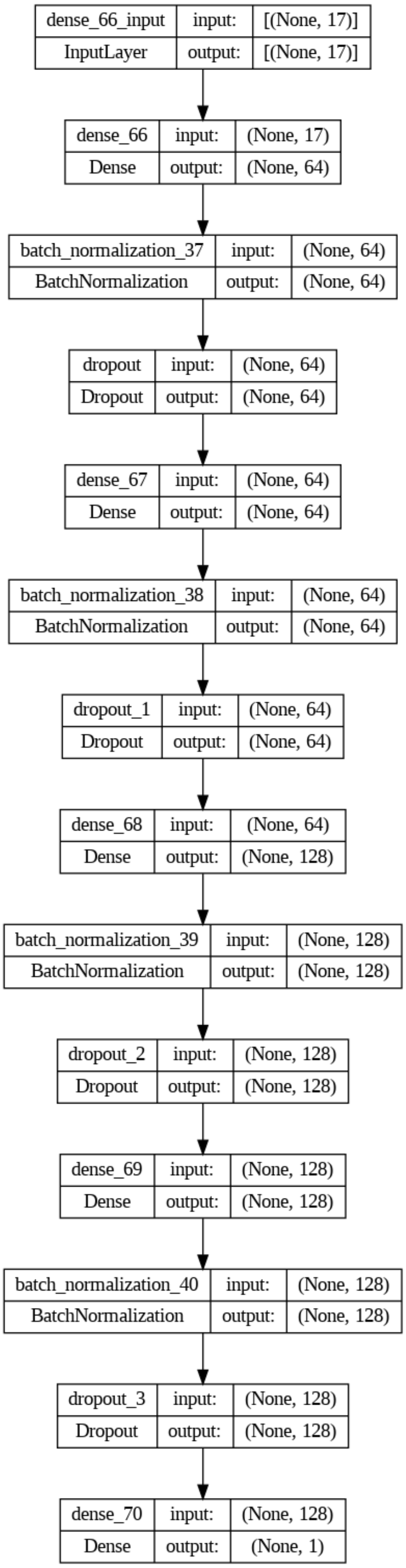

Figure 6: Architecture of DNN

To create benchmark for measuring models' performance, we conduct the baseline model for experiment set 1 by finding the difference between data of 2021 and 2020 using notch distance methodology. After that, we normalize the result using min-max normalization and finding MAE of the baseline model which is 0.078. The baseline model for experiment set 2 is unable to create as we used 8 unseen companies for the test set and the previous year rating data of the certain companies is not available.

We analyze the mean absolute value of three models between the experiment set 1and the experiment set 2. Firstly, we observe that the linear regression model has the highest mean absolute value, followed by the SVM and the DNN models for both experiments. This MAE value indicates that the DNN model outperforms other models in accuracy. Comparing the two experiments, all three models presented higher mean absolute values for the adjusted data set in the second experiment.

This MAE value indicates that all three model portray a higher predictive ability for the data set in the experiment set 1. The result of MAE is shown in table 12.

Model	Experiment Set 1	Experiment Set 2
Baseline	0.078	Not available
SVM	0.160	0.180
Linear Regression	0.161	0.202
DNN	0.157	0.170

Table 12: Comparison of MAE between experiments

For the SVM model, both experiments have a mean absolute error of around 0.160 to 0.180. Our prediction has an average loss of 0.160 and 0.180. Therefore, the actual value can be predicted with a mean error of 0.160-0.180% of the true value. For the linear regression, both models have a mean absolute error of around 0.161 to 0.202. Our prediction has an average loss of 0.161 and 0.202. Therefore, the actual value can be predicted with a mean error 0.161-0.202% of the true value. For the DNN model, both models have a mean absolute error of around 0.157 to 0.170. Our prediction has an average loss of 0.150 and 0.170. Therefore, the actual value can be predicted with a mean error of 0.150-0.170% of the actual value.

We analyzed the MSE graph between the experiment set 1 and the novel approach of adjusting the training set and test set by comparing training loss (loss) to the validation loss (val_loss). The distinct patterns in the Mean Squared Error (MSE) graphs for linear regression and deep neural network (DNN) models are observed.

For the linear regression model, the MSE graph in figure 7 and figure 8 present trend for validation loss and training set for experiment 1 and experiment 2. It can be clearly observed that the graph of both experiments exhibit convergence which indicates that the model's performance improves consistently throughout the training process. This indicates that the linear regression provides a good predictive performance for both experiment set 1 and experiment set 2.

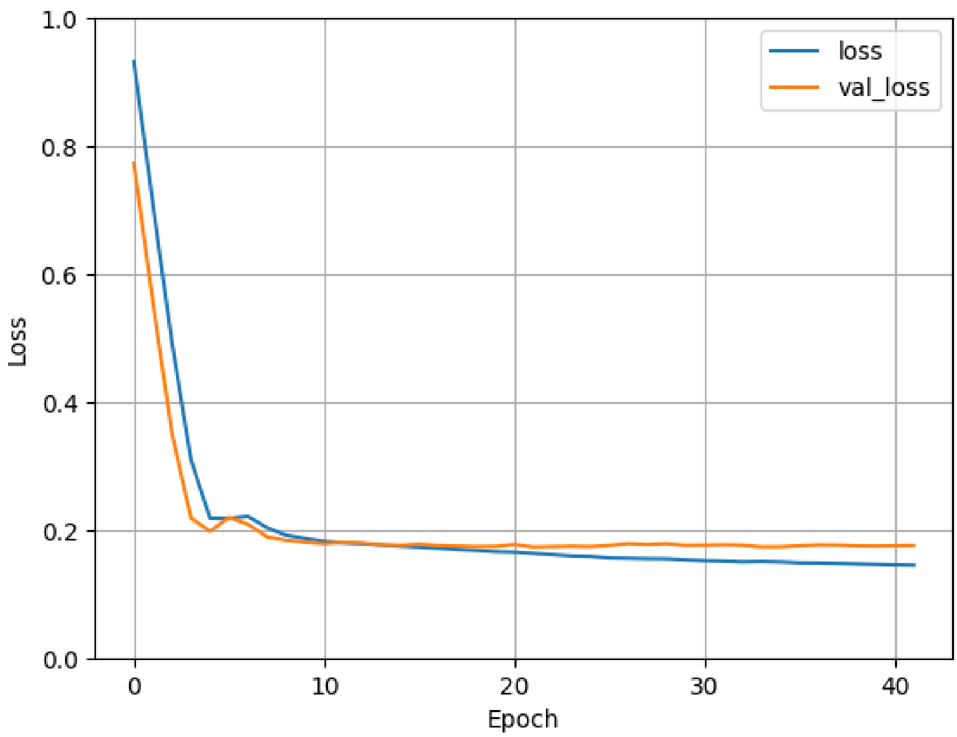

Figure 7: MSE graph of the linear regression model for the experiment set 1

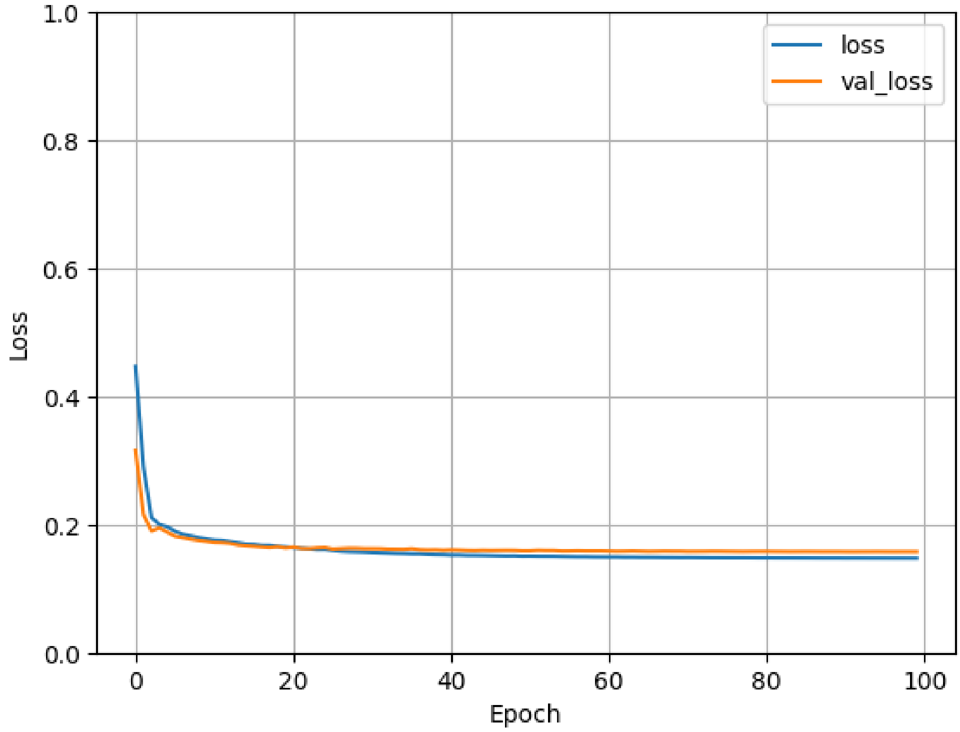

Figure 8: MSE graph of the linear regression model for the experiment set 2

The DNN model similar to the linear regression model has demonstrated a likeable behavior of converging. The MSE graph for the DNN model in figure 9 and figure 10 with training loss (loss) and validation loss (val_loss) in both experiments showed a clear convergence pattern with a consistent decrease over the epochs. This trend indicates that the DNN model was able to learn and adapt to the new adjusted data set, progressively reducing the disparity between predicted and actual values. The convergence of the MSE graph suggests that the DNN model achieved a stable and desirable level of performance. However, the MSE graph of DNN model for the experiment set 2 has shown the earlier sign of convergence compared to the experiment set 1. Therefore, it can be concluded that the DNN model perform better with the experiment set 2.

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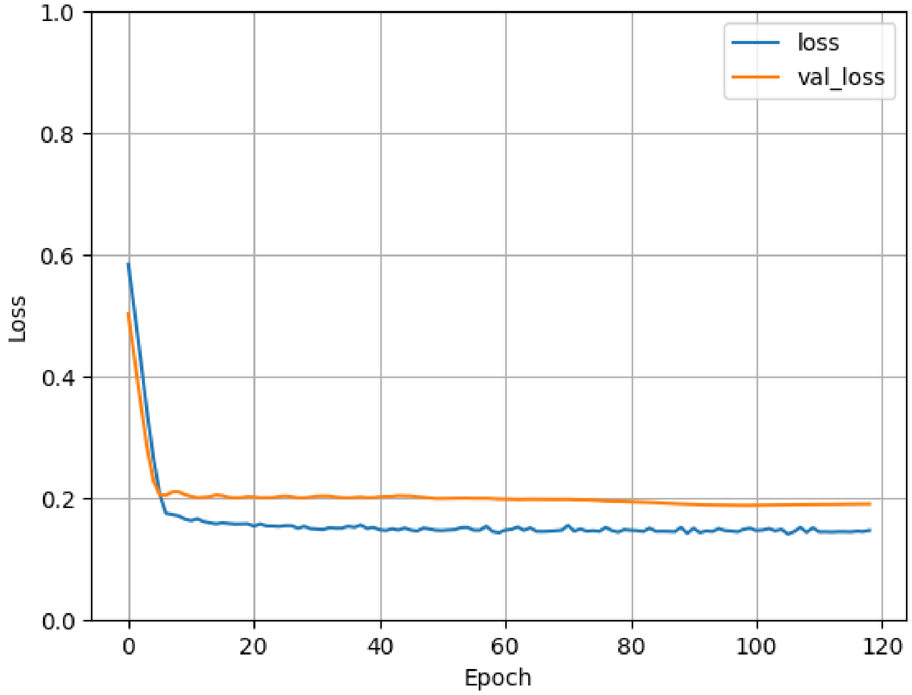

Figure 9: MSE graph of the DNN model for the experiment set 1

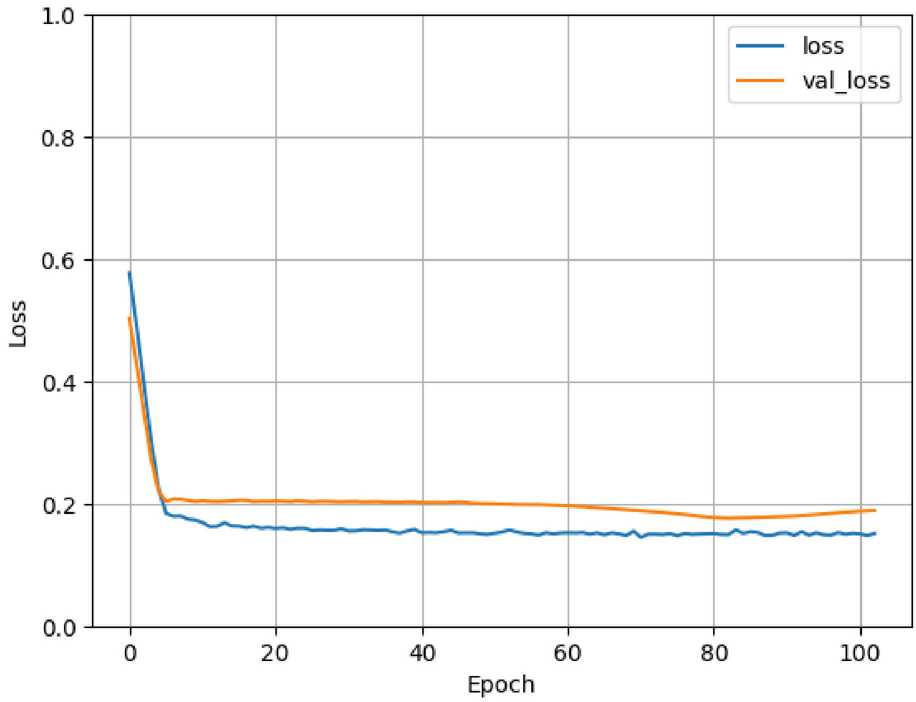

Figure 10: MSE graph of the DNN model for the experiment set 2

Chapter 6 Discussion

For both experiment set 1 and experiment set 2, we observe the MAE values of the three models of SVM, linear regression, and DNN. By using the baseline model for experiment 1 to compare with the models' performance, we found out that the MAE of the baseline model at 0.078 is lower than the MAE result of all three models. Therefore, the baseline model provides higher predictive ability compare to all three models for experiment 1.

For experiment 2, as the baseline model is not able to conduct for this specific case, our models are still applicable to use in this certain situation and DNN model has presented the highest predictive ability compare to the SVM model and the linear regression model. From the MAE result, the DNN model has shown value of 0.170, following by the SVM at 0.180, and the linear regression model at 0.202. In addition, by observing the MSE graph for experiment 2 of both linear regression model and the DNN model, it can be clearly seen that the graphs present a convergence pattern which reflect that both models able to learn and adjust to the new data set and offer a good predictive performance.

We later applied the notch distance concept to observe models' prediction of experiment 2 by finding the difference between actual and forecast values of credit rating prediction. For example, the credit rating of AAA and AA+ differs by one notch. In an actual situation, when the committee of a rating agency reviews the credit rating of entities, which is done annually, the rating typically increases or drops by one to two ratings. Therefore, the prediction error of not over two rating differences, two notches, is considered to be acceptable. For experiment 2, it was found that the models have a prediction error of not over two notches by 73%. This suggest that the model has correctly predict 73% of the test set for experiment 2.

To further investigate the model's prediction, we have observed that the credit rating with prediction error over two notches has actual rating falls in non-investment grade and in the range of AA to AAA. This prediction error can be explained by the fact that data distribution over non-investment grade and credit rating of AA to AAA is smaller than the total of 300 data set.

Credit Rating	Amount of Data from Annual Financial Statement	Percentage compares to total data
AA to AAA	29	10%
Non-investment grade (BB and BB+)	22	7%
Total data	300	100%

Table 13: Distribution of data for over two notches prediction error

The experiment set 2 has selected eight unseen companies, twelve data, with data available only in 2020 and 2021 as the test set. By observing the 27% of prediction error over two notches, it is found that companies present credit rating in range of AA to AAA and non-investment grade which agrees with the insufficient credit rating data distribution over two classes.

Further progress is suggested on an expanded period of the data set as to obtain more data. This research has used five years historical data which correspond with the actual rating consideration which financial projection model is conducted over 3-5 years and also focus on longer period of time compare to other works. The selection of better credit rating data distribution for the training set and the test set is required as the disproportionate of data distribution for each credit rating class can result in model fail to track pattern of each rating transition. The suggestion is to select five to ten companies for each rating class in order to cover credit ratings of non-investment grade to see the pattern of rating transition from investment grade to non-investment grade. This will allow the model to monitor risky companies and give an early warning sign before the rating transition occurs.

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Chapter 7 Conclusion

In conclusion, corporate credit ratings serve as important indicators of a company's health, performance, and viability for potential investors. However, due to challenging economic circumstances, businesses often face difficulties, and the transition of credit ratings may not keep up with the rapidly changing real-life situations. This can lead to investors being unable to adjust their investment strategies, resulting in financial losses.

In the field of predicting corporate credit ratings, various techniques have been employed, including decision trees, Support Vector Machines (SVM), linear regression, and neural networks. This research has utilized three machine learning models to address this issue. The dataset consisted of 17 financial ratios and credit ratings spanning from 2016 to 2021, obtained from SETSMART and TRIS rating agency.

This study conducts two experiments to assess models' performance based on previously acquired knowledge of data labeling and normalization techniques. The experiment set 1 purpose to use all the existed rating information of the companies to train models for prediction rating of the same group of companies in the next year. The experiment set 2 used existed rating information of the companies to predict the rating of companies that are not in training set, but in the same period. This was done by considering companies consist of rating data available for the years 2020 and 2021 only to be completely unseen by the models. The result suggests that experiment 2 is applicable for the situation. The DNN model offer a better performance observing from MAE and MSE result. Further research on model predictive ability and tuning for better performance can be done to achieve better result.

Overall, this research contributes to the field of corporate credit rating prediction by demonstrating the performance of machine learning models and highlighting the importance of data preprocessing techniques and model configuration. The findings emphasize the need for accurate and timely credit rating predictions to assist investors in making informed decisions in an ever-changing economic landscape.

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